Shadow Reclassification

in Aerial-Imagery by Correlation of Spectral Compositions

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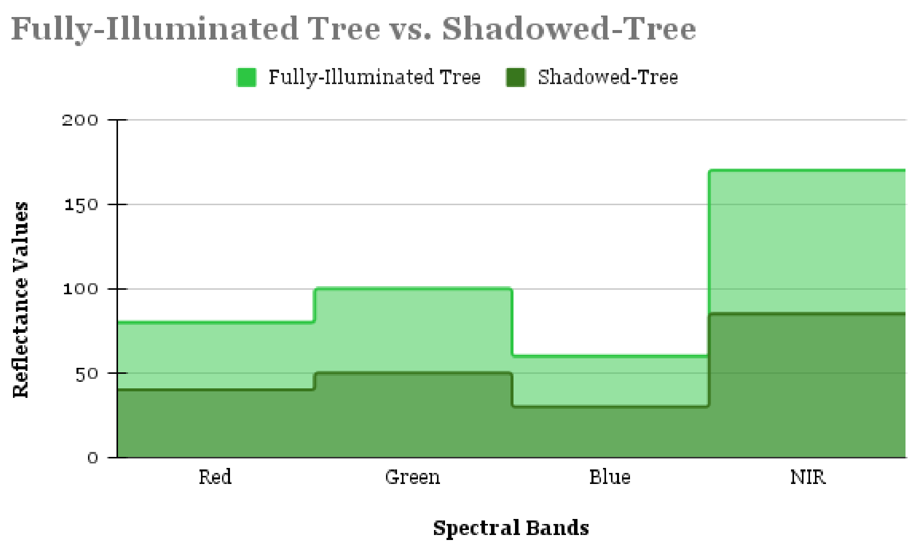
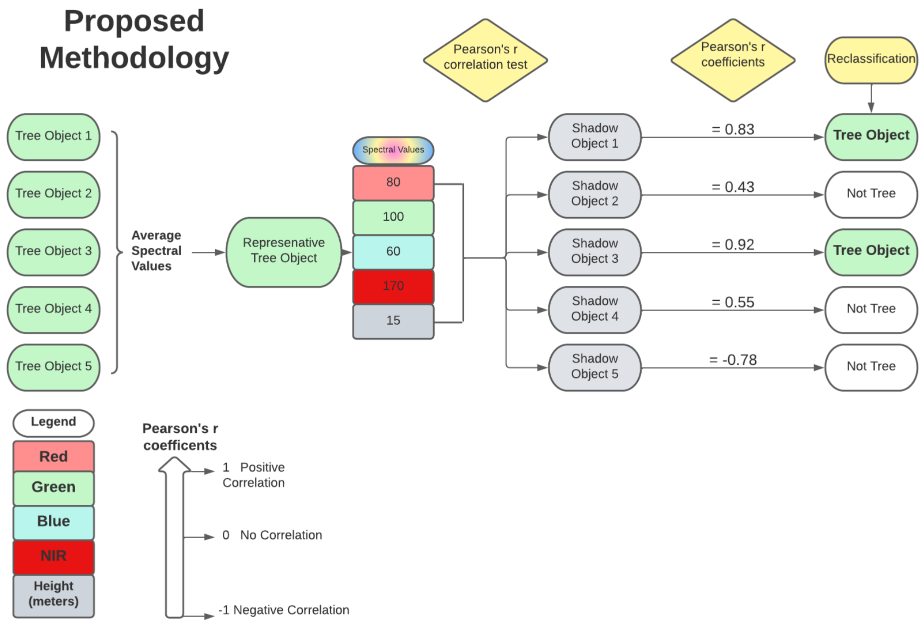
Introduction

In OBIA, land cover classifications are undermined by shadows inherent in remotely sensed imagery. In the context of urban mapping, a significant portion of the scene can be hidden, resulting in inaccurate land cover measurements which could affect urban development, utility planning, and or environmental mitigation. As land cover mapping utilizes higher spatial and radiometric resolutions by means of aerial or drone imagery, shadows are more detectable but also pose a greater challenge when attempting to ameliorate these shadowed-areas. When classifying a map using an OBIA-approach, developing a conditional ruleset for each class becomes a challenge when attempting to derive what that land cover's spectral composition is like in a shadowed area. In fact, it might be impossible to accommodate these deviations in the initial classification and therefore, shadows are left in a class of their own.

The key is that although shadows have a different intensity when compared to fully-illuminated areas in a scene, the land cover's spectral composition remains constant regardless of the intensity of those spectral signatures. [example of tree land cover class]



My solution to this problem is therefore to derive correlation coefficients that can help identify spectrally-similar objects based on a high correlation value. By correlating spectral compositions within shadows to spectral compositions of known land cover types, land cover beneath shadows can be reliably predicted. My proposal entails using the Pearson's r correlation test to match unknown shadowed objects to a sample size of known land cover classifications based on the objects' spectral metrics. By identifying which shadow-objects are most similar to any given land cover class, a simple reclassification can then be used to remove the shadows, leaving the true land cover class that is actually underneath them.



NAIP multi-spectral imagery

For my capstone proposal I will be working with NAIP aerial imagery of 1-meter spatial resolution. This imagery has 4 bands: Red, Green, Blue, and Near-infrared. The imagery will be of Boulder, Colorado encompassing a 3.75 x 3.75 minute tile which is approximately a 4x4 mile extent. Boulder, Colorado is a small-sized city which is primarily made up of residential neighborhoods and outlets. The area has a small downtown area with medium-sized structures and the largest structures found in the scene come from the campus of the University of Colorado. Subsequently this is where the largest shadows are concentrated. Conversely however the majority of shadows come from dense residential vegetation.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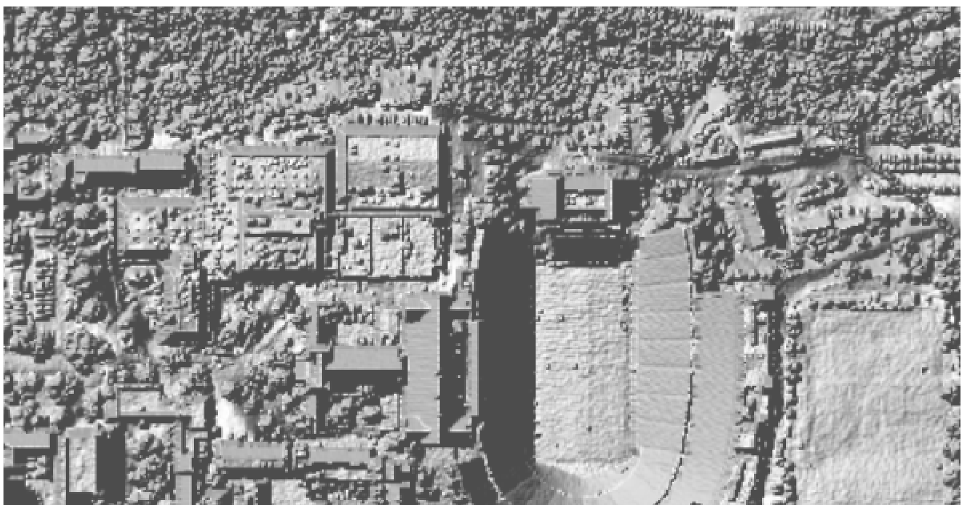
Digital Surface Model (DSM) - built from Lidar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DSM

I chose this as my study area as it is the city that I live in and allowed me to test my methodology by obtaining locations of shadows in the imagery and recording the land cover beneath them. A total of 100 ground truthed shadowed areas have been recorded already and for the final project I hope to obtain a sample size of close to 500. This will allow me to test my hypothesis of using the Pearson's r correlation test at a significant level and assess its accuracy. However, to test the efficacy of my proposal I used the initial 100 ground truthed shadowed objects to present the methodology in action and its performance. The remainder of my presentation will be showing the general workflow of the methodology and the results I came up with.

Workflow

Initial Classification

The initial classification would be conducted in eCognition using an OBIA-approach to properly classifying our land cover classes. A segmentation process would be used to accurately segment the NAIP imagery to accurately represent spectrally-similar regions. A conditional rule set would be developed to identify the characteristics of each land cover class.

Land Cover Classes

Buildings Pavement Trees Grass Bare Earth Shadows

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Accuracy Assessment

ERROR MATRIX	Bare Earth	Buildings	Grass	Pavement	Shadows	Trees	U. Accuracy
Bare Earth	89	3	0	2	2	0	93%
Buildings	2	89	0	5	0	0	92%
Grass	0	0	92	0	0	1	98%
Pavement	2	0	0	81	0	0	97%
Shadows	0	0	0	0	90	1	98%
Trees	0	0	8	0	2	98	90%
Unclassified	7	8	0	12	6	0	539
P. Accuracy	89%	89%	92%	81%	90%	98%	600

Overall Accuracy: 90%

Extract Object Metrics

Key Metrics:

- Red
- Green

- Blue
- NIR
- Standard Deviation of nDSM ~ Surface Type Indicator
- nDSM ~ Height Indicator
- NIR / Red ~ Impervious/Pervious Indicator
- NIR - Red ~ Illuminated Normalization
- NDVI ~ Impervious/Pervious Indicator
- GLCM Homogeneity ~ Smoothness Indicator

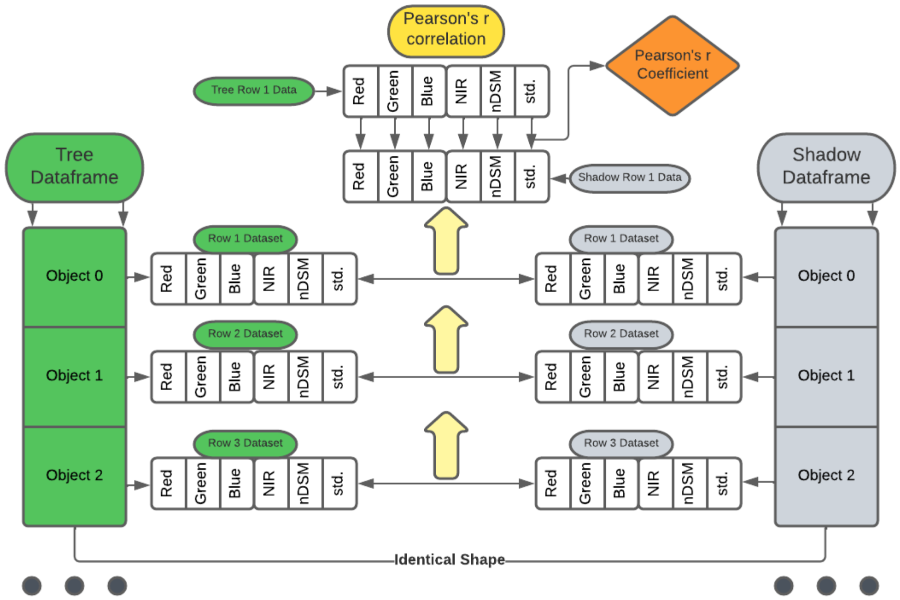
Correlation Tests using Ground Truth Points

Shadow_point_ground_Truth

Python Data Analysis Library (pandas as pd) with spatial extension (geopandas as gpd)

pd.corrwith(axis=1)

Pairwise correlation on columns (ROW-WISE)



Jupyter Notebook

Data Cleaning, Correlation, Results

Results:

C_Corr_rework

Final Results

Error Matrix

ERROR MATRIX	Bare Earth	Buildings	Grass	Pavement	Trees	U. Accuracy
Bare Earth	2	0	0	0	0	100%
Buildings	0	3	0	0	1	60%
Grass	0	0	20	6	0	100%
Pavement	0	0	0	51	0	100%
Trees	0	0	4	0	4	50%
Unclassified	0	1	1	6	1	80
Total	2	4	25	63	6	100
P. Accuracy	100%	75%	80%	81%	67%	

Overall Accuracy: 80%

Challenges

- Shadow-Object Selection Overlap
    - Example: *A Shadow Object is selected as both Tree and Building class*
    - Potential Solution: **Capture each shadow-objects proposed selection and rerun correlation test on objects with more than one Class. Correlation can can be rerun multiple times to choose Class with highest selection rate.**
- Processing speeds slow down and dealing with shapefile size capacity
    - Example: *Scaling up to full NAIP tile*.
    - Potential Solution: **Tile NAIP imagery into four parts. Keep Shadow Objects below 1 million.**

Next Steps

- Refine Python code to accommodate for multiple Class selections.
- Tiling NAIP to scale workflow.
- Assess accuracy at scale.
- Assess accuracy in another study area.